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Article

Investigating determinants of credit growth in the case of Kosovo: A VAR model

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Abstract: This paper investigates the factors influencing credit growth in Kosovo, focusing on the relationship between credit activity and key economic variables, including GDP, FDI, CPI, and interest rates. Its analysis targets loans issued to businesses and households in Kosovo, employing a VAR model integrated into a VEC model to investigate the determinants of credit growth. The findings were validated using OLS regression. Additionally, the study includes a normality test, a model stability test (Inverse Roots AR Characteristic Polynomial), a Granger causality test for short-term relationships, and variance decomposition to analyze variable shocks over time. This research demonstrates that loan growth is primarily driven by its historical values. The VEC model shows that, in the long run, economic growth in Kosovo leads to less credit growth, showing a negative link between it and GDP. Higher interest rates also reduce credit growth, showing another negative link. On the other hand, more foreign direct investment (FDI) increases credit demand, showing a positive link between credit growth and FDI. The results show that loans and inflation (CPI) are positively linked, meaning higher inflation leads to more credit growth. Similarly, more foreign direct investment (FDI) increases credit demand, showing a positive link between FDI and credit growth. In the long term, higher inflation is connected to greater credit growth. In the short term, the VAR model suggests that GDP has a small to moderate effect on loans, while FDI has a slightly negative effect. In the VAR model, interest rates have a mixed effect: one coefficient is positive and the other negative, showing a delayed negative impact on loan growth. CPI has a small and negative effect, indicating little short-term influence on credit growth. The OLS regression supports the VAR results, finding no effect of GDP on loans, a small negative effect from FDI, a strong negative effect from interest rates, and no effect from CPI. This study provides a detailed analysis and adds to the research by showing how macroeconomic factors affect credit growth in Kosovo. The findings offer useful insights for policymakers and researchers about the relationship between these factors and credit activity.

Keywords: credit growth; GDP; Kosovo; VECM; bank

1. Introduction

The banking sector is absolutely critical to economic stability, being one of the most important drivers of economic activity. Banks provide credit, helping businesses and households invest and spend more—factors important to a country’s economic growth. To keep the economy stable, it is necessary to understand what affects credit growth. This paper will particularly focus on the case of Kosovo, a small developing country with a bank-based financial system. The banking system mostly consists of foreign-owned banks and a few local actors, with major players including NLB Group, Raiffeisen Bank Kosova, Procredit Bank Kosova, TEB SH. A, and Pri Bank Kosova.

Despite the significant role of credit in the economy of Kosovo, literature that evaluates the factors that could impact credit is non-existent. Existing literature on neighboring countries finds that factors like GDP, inflation, and deposits significantly impact credit growth. Shijaku and Kalluci (2014), while investigating the determinants of credit growth in Albania's case, argue that there is a positive relationship between economic development and credit growth. Ivanovic (2016) reveals that a positive economic development followed by an increase in the bank's deposit capacity leads to higher credit growth for a country. Similarly, Shingjergji and Hyseni (2015), who analyzed the influence of some macroeconomic and banking factors on credit growth in the case of Albania, concluded that there is a positive relationship between credit growth, GDP growth, inflation rate, and capital adequacy ratio. On the other hand, credit growth is negatively related to factors such as unemployment rate, bank size, non-performing loans, and interest rates.

Given the similarities among Kosovo and its neighboring countries regarding economic development, it is quite reasonable to assume that these findings could also apply to Kosovo's case. However, this assumption has not been empirically verified. This paper aims to evaluate the relationship between credit activity in Kosovo and some key economic factors such as Gross Domestic Product (GDP), Foreign Direct Investment (FDI), Consumer Price Index (CPI), and Interest Rates (IR). Particularly, the objectives are:

1) To determine whether these economic factors have a causal effect on credit growth and, if so, whether the effects are positive or negative,
2) To examine if the relationships between credit growth and these variables hold in the short term or long term, providing insights into the dynamics of credit growth over time, and
3) To contribute to the literature by addressing a gap in studies on credit growth determinants in Kosovo, as existing research primarily covers neighboring countries.

This study offers a fresh perspective by focusing on Kosovo, a developing country with a bank-based financial system dominated by foreign-owned banks. Our research looks at important economic factors that have not been studied in this way before. We hope it will help scholars and decision-makers alike better understand credit growth and its effects on the economy in the region. The research questions in the methodology section guide a detailed analysis of what affects credit growth in Kosovo, helping to improve understanding of this topic both nationally and regionally.

The remaining segments of this paper are as follows:

1) A literature review regarding factors that influence credit growth,
2) An explanation of the methodology used and a summary of the research questions of the paper,
3) The empirical results of the research and their interpretation,
4) A discussion of the findings, and
5) A conclusion and some key insights and recommendations for future research regarding credit growth in Kosovo.

2. Literature Review

2.1. Introduction to the banking sector in Kosovo

The banking sector in Kosovo has shown consistent growth and resilience, even during international market volatility, the global financial crisis, and the EU debt crisis. According to the Financial Stability Report of the Central Bank of Kosovo (2023), the country's financial stability improved despite challenges like inflation and a weaker economic outlook. Dominated by EU-based foreign banks, Kosovo's banking sector saw its assets grow by 13.5% in 2022, reaching €6.7 billion, with total deposits increasing by 13.3% in the same period.

Credit activity also reached its highest growth rate in eleven years, driven primarily by credit demand for inventory, working capital, and fixed investments. On the supply side, factors like strong liquidity, competition, and help from the Credit Guarantee Fund of Kosovo were important. For households, credit demand was driven by spending needs and expectations about the real estate market. By the end of 2022, active loans totaled €4.35 billion, a 16.1% increase, although the market for new loans experienced a slowdown, returning to pre-pandemic levels.

2.2. The relationship of credit growth with other macroeconomic and bank-specific factors

2.2.1. Autoregressive distributed lag econometric model

Lazarov et al. (2023) investigated the bank and macro-specific determinants that lead to credit growth in the private sector in North Macedonia. Their study incorporates the ARDL model, and its results reveal that deposits and bank efficiency significantly impact loan growth in the private sector in North Macedonia. The study also finds a negative link between loan growth and non-performing loans in the private sector. Assel et al. (2024) studied how factors like real wages, inflation, and consumer spending affect bank lending in Kazakhstan. Their findings show that real wages and inflation are key factors in lending activity. Their regression analysis shows that areas with higher real wages create better conditions for banking growth, highlighting the strong link between real wages and bank lending. However, the study also points out a weaker connection between real wages and overall banking sector growth.

Baoko et al. (2017), using the Autoregressive Distributed Lag model on data from 1971 to 2011 for the case of Ghana's economy, examined the determinants of bank crediting. The results of the paper reveal that factors such as real lending rate, money supply, bank deposits, and bank assets are significantly related to credit growth in the long run. As for the short run, the study implies a positive relationship between credit growth and inflation. Finally, the paper also reveals that an increase in bank deposit mobilization does not necessarily lead to an increase in the credit supply in the private sector. The study concludes that to boost lending and credit demand, the central bank should require lower reserves from the commercial banks.

2.2.2. Vector error correction model

Thierry et al. (2016) studied the link between bank credit and economic growth using data from Cameroon. They used different statistical methods, tests, and a Vector Error Correction Model to analyze this relationship. The model implies a unidirectional relationship from domestic credit to the private sector and bank deposits to gross domestic product per capita (GDPPC). The study also implies that monetary policies favoring bank credit will lead to a further increase in the economic growth of Cameroon. Akani and Onyema (2017) examined Nigeria's credit growth determinants. The study incorporated three multiple regressions to conduct the analyses and examine the effect of macroeconomic, monetary policy, and international variables on credit growth in Nigeria. The paper's results show that from the macroeconomic variables, there is a negative relationship between public expenditure, inflation rate, capital formation, and credit growth. In contrast, the paper identifies a positive relationship of credit growth with variables such as real gross domestic product, government revenue, and balance of payment. From the perspective of monetary policy variables, treasury bill rate, interest rate, and compliance with credit rules hurt domestic credit. In contrast, other variables such as monetary policy rate, financial deepening, and broad money supply growth positively impact credit. Finally, for the international variables, the study reveals a positive relationship between credit growth, the exchange rate, international liquidity, foreign direct investment, and openness of the economy, as well as a negative relationship between credit with cross-border credit and net foreign portfolio investment.

Petkovski et al. (2016) investigated the credit growth in Macedonia and how the credit growth contributes to financial development. The study incorporates a two-sided approach to evaluate the credit growth in Macedonia. First, the statistical approach based on the deviations of the Credit/GDP ratio in the long-run trend is used, while the second approach to be applied is the error correction model. The paper shows that economic activity and bank deposits influence credit growth. The paper points to the great importance of the deposits in the credit growth of the Republic of Macedonia. Applying a Vector Error Correction Model, Shijaku and Kalluci (2013) evaluated the long-run determinants that lead to bank credit in the case of Albania. The study finds a positive relationship between bank credit and economic growth: Higher economic growth means higher credit growth. Considering the non-performing loans, this research shows a negative relationship between credit growth and NPLs. A decrease in non-performing loans increases the availability of bank loans. The research concludes that financial policies to reduce non-performing loans are important for increasing credit growth.

Additionally, Perez (2017) studied the factors affecting lending growth in Belize. The study incorporates some restrictions to detect the relationship between credit demand and supply; therefore, the results imply a long-run relationship between credit growth and domestic bank equity. In addition, due to regulatory capital rules and credit risk reduction, a long-run relationship exists between credit growth and non-performing loans. Otto (2020) analyzed the impact of COVID-19 on domestic credit in China. Results of the study claim that increases in COVID-19 cases/deaths point to an increase in domestic credit in the short and long run. Al-Shammari and El-Sakka (2018) examined the determinants that lead to credit growth in the private sector across some of the OECD countries. A data set of 34 countries on the period of 2001 to 2013 is incorporated in the research; it reveals that in the long run trend, factors such as exchange rate, money supply, interest rates, foreign liabilities inflation, fixed capital formation, and GDP and are the main determinants that lead to credit growth over the

OECD countries. The study implies that macroeconomic stability is essential for the credit flow.

2.2.3. GMM estimator

Bilgin et al. (2020) used the two-step system generalized method of moments (GMM) estimator to study the impact of economic uncertainty on credit growth in GCC countries from 2012 to 2019, comparing Islamic and conventional banks. Their paper's results suggest that an increase in economic uncertainty immediately leads to a decrease in credit growth in the case of conventional banks. However, economic uncertainty did not significantly affect Islamic banks' credit growth. Gozgor (2014) investigated the determinants of domestic credit growth in 61 developing economies; hence, the paper's results reveal a positive relationship between income, money supply, and domestic credit. On the other hand, the study also reveals a negative impact on interest rates and current account balances in domestic credit. Albaity et al. (2023) analyzed whether confidence, trustworthiness, and governance quality impact the credit growth of the Gulf Cooperation Council (GCC). Moreover, they also compared Islamic and conventional banks and whether credit growth differed between the two kinds of banks. The study's results suggest a positive relationship between trustworthiness and credit growth. In terms of conventional and Islamic banks, the study points out that loan growth was more noticeable for Islamic banks.

Pasaribu and Mindosa (2021) investigated the specific determinants of bank credit growth and stability by giving evidence from commercial banks in Indonesia. The study covers over 89% of Indonesia's commercial banks, covering 2002–2018. Primarily, the paper focuses on examining credit growth determinants and gives evidence on the consequences of excessive credit growth on the overall stability of banks. The study states that deposit growth is the most important variable that remains robust after checking for bank size and observation period; therefore, banks are very dependent on consumers' deposits, and consumers are more aware of how to manage their money. The authors say the second most important factor is the gross non-performing loan ratio, which strongly impacts loan growth in both good and bad times. Banks with many non-performing loans are less likely to lend in any economic situation. Furthermore, the study points out that liquidity is more important than capitalization; therefore, regulators should prioritize the liquidity ratio rather than capitalization to boost credit growth. Jackowicz et al. (2017) investigated the interaction of banks' lending dynamics, crisis phenomena, and ownership structure in banking systems in Central and Eastern European (CEE) countries. The study incorporated a panel set of more than 400 banks from 1994–2010. The results imply that the relationship between ownership structure and credit dynamics depends on the crisis type, whether it is a home, global, host, or simultaneous crisis. Regarding the bank-specific determinants, the study results show that deposit growth and profitability ratios are significant factors that impact credit growth in CEE countries in normal economic periods and crisis times.

2.2.4. Panel data regression

Drozdowska and Witkowski (2021) examined the determinants of credit growth for banks in 20 countries of post-communist Central, Eastern, and South-Eastern Europe (CESEE). The study focuses on foreign-owned banks and the background of all bank operations in this part of Europe. The study's results reveal that bank behavior determinants remain the same regardless of bank ownership, the period, and the EU membership. Kouretas and Pawłowska (2020), through their empirical study and incorporating a panel data set model, also investigated the determinants that lead to credit growth for the case of 11 CEE countries. The study covers the period after the crisis of 2007–2009 and considers the market structure and the presence of foreign banks. Results from the paper establish that market structure and the development of the banking sector have a positive relationship and that both determinants significantly impact credit growth. The authors also investigated the impact of interest rates on credit growth, and the results show a significant effect of interest rates on the creditworthiness of households and businesses in general. Hai et al. (2024) analyzed the factors influencing bank lending in Vietnamese banks from 2012 to 2020. Results of the paper indicate that deposit growth, net interest margin ratio (NIM), and GDP growth positively impacted credit growth. In contrast, non-performing loans, bank size, and inflation negatively impact credit growth. Mihaylova-Borisova (2023) also analyzed the factors that impact the bank's credit on the private sector and households in CEE countries. According to the results of the empirical study, there is a positive relationship between GDP and credit growth, meaning that the real GDP in credit has a positive impact. In addition, the level of non-performing loans and deposits also appears to impact the given countries' credit performance significantly. Jovic and Jandric (2016) investigated the determinants of credit growth in Bosnia and Herzegovina from 2000 to 2015. The study incorporated the panel analysis, and the empirical results found that non-performing loans, inflation, deposits, and GDP growth greatly impact the credit growth rate. Drozdowska and Witkowski (2016) considered novel variables, such as crisis dummies, the financial safety net index, and ruling party dummies, which investigated the credit growth determinants in Central, Eastern, and South Eastern Europe (CESEE). The paper's results reveal that bank ownership is a significant determinant of credit growth. State-owned banks are the most expansive in regards to credit growth. This research also suggests that crisis harms credit growth, although there have not been many crises in such countries.

2.2.5. Multiple linear regression

Cantú et al. (2022) analyzed the bank characteristics in five Latin countries (Brazil, Chile, Columbia, Mexico, and Peru) and how these characteristics affected the credit growth of such countries. The paper's findings reveal that well-capitalized and larger banks with low-risk indicators and a stable funding source generally issue more credit. Abuzayed et al. (2023), by incorporating a sample of 7235 banks from 160 countries, analyzed the interaction between corruption, lending, and bank performance. The study determined that corruption increases bank lending; however, this harms bank profitability and increases risks. According to the study results, corporate lending is mostly impacted by corruption. In addition, bank-level corruption has also been found to impact the performance of banks in both developed and emerging economies. Alihodžić and Eksi (2018), using a multiple regression analysis, investigated the factors that impact the credit growth in some Western Balkan Countries and credit policy in Turkey. The regression results for all the countries show that more non-performing loans lead to slower credit growth. A high percentage of non-performing loans makes banks less willing to take risks and reduces credit growth. In addition, the empirical results from the regression show evidence of a positive relationship between credit growth and economic growth. Similarly, the study found a positive relationship between deposit growth and credit growth. Norawati et al. (2022) investigated the factors determining credit growth in Indonesia. The study incorporates multiple regression with probit analysis therefore the results suggest that controlling third-party funds and operational costs are significant determinants that impact credit growth. There is a positive relationship between these variables and credit growth. Awdeh (2017) analyzed the determinants of credit growth in Lebanon. The analysis section consists of 34 commercial banks, with the paper finding that GDP growth, deposit growth, inflation, and money supply boost credit growth in the private sector. On the contrary, interest rates, public borrowings, remittances, and T-bill rates lead to decreased credit growth.

3. Methodology

3.1. Brief description of data and a summary of research questions

The data incorporated in this paper are publicly accessible in the Central Bank of Kosovo and the Agency of Statistics of Kosovo. The dataset covers 2013 to 2023 and is expressed quarterly, resulting in 45 observations. Considering that the CPI indicator is expressed as a percentage and the other variables are expressed in EUR, a logarithm in the other variables is applied to ensure comparability. Finally, frequency conversion is applied to align all variables in the same frequency. The analysis was done using EViews 12 SV software, which is suitable for time-series analysis. However, the model has some limitations, so certain advanced tests and checks could not be performed. Despite these restrictions, the methodology applied provides meaningful insights into the relationships between the variables while ensuring statistical rigor within the limits of the data and software capabilities. **Table 1** includes the questions posed by the researchers. **Table 2** represents a summary of the variables in the study.

Table 1. Research questions.

Variable Pair	Question Range
Loans (X) and GDP (Y)	Q. 1-4
Loans (X) and FDI (Y)	Q. 5-8
Loans (X) and IR (Y)	Q. 9-12
Loans (X) and CPI (Y)	Q. 13-16
Questions	Question Nos.
Does X Granger cause Y?	Q. 1, 5, 9, 13
Does Y Granger cause X?	Q. 2, 6, 10, 14
Is there a bi-directional relationship?	Q. 3, 7, 11, 15
Is there a long-term relationship?	Q. 4, 8, 12, 16

Table 2. Summary of variables.

Variables	Frequency	Date Range	Source
Loans	Quarterly	2013–2023	Central Bank of Kosovo
GDP	Quarterly	2013–2023	Central Bank of Kosovo
FDI	Quarterly	2013–2023	Agency of Statistics Kosovo
Interest Rates	Quarterly	2013–2023	Central Bank of Kosovo
CPI	Quarterly	2013–2023	Agency of Statistics Kosovo

3.2. Econometric model—VAR model

This study addresses the research questions and objectives outlined in the previous section. A standard Vector Auto-Regressive (VAR) model is first applied and later integrated into a Vector Error Correction Model (VECM) to address its limitations. Within the VECM framework, a variance decomposition test is conducted. Sims (1990) introduced the VAR econometric model, which treats all variables in a system as potentially endogenous, offering an alternative to large-scale structural equation models. VAR relies on lagged variables that appear only on the right-hand side of equations, enabling the detection of Granger causality among variables (Brooks, 2008; Granger, 1981). Hansen and Johansen (1999) highlighted the model's practicality for estimating macroeconomic changes and economic forecasting. Similarly, Gujarati and Porter (2009) emphasized its flexibility and simple generalization. Among the forms of VAR, the bivariate VAR is the most common, involving two variables, Y_{1t} and Y_{2t}, whose values depend on combinations of their previous values and error terms:

$$Y_{1t} = \beta_{10} + \beta_{11}Y_{1t-1} + \cdots + \beta_{1k}Y_{1t-k} + \alpha_{11}Y_{2t-1} + \cdots + \alpha_{1k}Y_{2t-k} + U_{1t} \tag{1}$$

$$Y_{2t} = \beta_{20} + \beta_{21}Y_{2t-1} + \cdots + \beta_{2k}Y_{2t-k} + \alpha_{21}Y_{1t-1} + \cdots + \alpha_{2k}Y_{1t-k} + U_{2t} \tag{2}$$

U_{it}, within this case expresses the error term, $E(U_{it}) = 0$, $(i = 1, 2)$, $E(U_{1t}U_{2t}) = 0$ (Brooks, 2014).

In this paper, stationarity and the same order of integration conditions must be met before ensuring the final VAR is stable. Stationarity refers to a stochastic process contributing to statistical stability. We use a unit root test to evaluate the stationarity characteristics of the series. The Augmented Dickey-Fuller test (Dickey & Fuller, 1979) will be used to assess the stationarity of the data. Moreover, if the data is not initially stationary, meaning it is not integrated into order zero, the first difference will be taken to ensure stationarity. The unit root test will then be reapplied. Thus, it will take this equation:

$$Y_t = \rho Y_{t-1} + u_t \text{ and test if } \rho = 1 \tag{3}$$

Having tested for stationarity, a cointegration test will be applied next. This test tracks if our variables co-move together. The Johansen test, which, according to Dwyer (2015), includes the Trace and eigenvalue tests, will be used to detect cointegration among variables. The null hypothesis for the test is as follows:

H0 = No cointegration

H1 = Cointegration

3.3. Granger causality

The Granger causality test is used to determine the direction of causality when two variables are related but the cause-and-effect relationship between them is unclear (Studenmund, 2014). Applying the VAR or VECM models instead of concluding the statistical significance of the coefficients, it is also possible to make further analysis, such as detecting which variable causes the other; thus, VAR and VECM models consist of Granger causality analysis (Granger, 1981). To apply the Granger causality test, we run the following equation:

$$Y_{1t} = \beta_{10} + \beta_{11}Y_{1t-1} + \cdots + \beta_{1k}Y_{1t-k} + \alpha_{11}Y_{2t-1} + \cdots + \alpha_{1k}Y_{2t-k} + U_{1t} \tag{4}$$

$$Y_{2t} = \beta_{20} + \beta_{21}Y_{2t-1} + \cdots + \beta_{2k}Y_{2t-k} + \alpha_{21}Y_{1t-1} + \cdots + \alpha_{2k}Y_{1t-k} + U_{2t} \tag{5}$$

Therefore, the hypothesis for the following equations are: H_0: $\alpha_{11} = \alpha_{12} = \ldots = \alpha_{1k} = 0$ and H_A: $\alpha_{11} \neq 0$ and/or $\alpha_{12} \neq 0$ … and/or $\alpha_{1K} \neq 0$. Given this statement, if the null hypothesis is rejected, it is possible to conclude that Y_2 granger causes Y_1. Testing for the other scenario whether Y_1 granger cause Y_2 we use the following hypothesis: H_0: $\alpha_{21} = \alpha_{22} = \ldots = \alpha_{2k} = 0$ and H_A: $\alpha_{21} \neq 0$ and/or $\alpha_{22} \neq 0$ … and/or $\alpha_{2K} \neq 0$. Being able to reject the null hypothesis means that Y_1 granger causes Y_2.

Considering the given hypothesis, Gujarati (2006) reveals various types of Granger causality. The types of causality include unidirectional causality, bidirectional causality, and independence (no Granger causality).

3.4. Vector Error Correction Model

As discussed in the above sections, the VAR model does not capture whether there is a short-run or long-run relationship among the given variables; thus, literature critiques this (Pesaran, 2015; Pesaran and Shin, 1998). However, based on the cointegration results, the study will proceed with the next step to address this matter. Thus, the VAR analysis is extended by adding the error correction term (Brooks, 2014). Adding the error correction term contributes to better and more appropriate results within the study. VECM describes the short-run relationship between variables apart from cointegration, which tests the long-run. Note that the lagged residual of the cointegration relationship is applied to the VEC (Brooks, 2014).

3.5. Ordinary Least Square model

The Ordinary Least Square regression is a fundamental econometric model that captures the relationship between dependent and independent variables. OLS minimizes the sum of squared residuals—the differences between observed and predicted values—resulting in the best-fitting line for the data (Brooks, 2008). The general form of the OLS regression is as follows:

$$Y_i = \beta_{10} + \beta_1 x_{1i} + \beta_2 x_{2i} + \cdots + \beta_k x_{ki} + \varepsilon_i \tag{6}$$

where:

Y_i is the dependent variable,
B_0 is the intercept,
$B_1, \beta_2, \ldots, \beta_k$ are the coefficients of the independent variables $x_{1i}, x_{2i}, \ldots, x_{ki}$,
ϵ_i is the error term, assumed to have a mean of zero and constant variance.

4. Discussion of the Results

4.1. Unit root test

To conduct a VAR and VECM model, the very first condition that the variables have to meet is the stationarity; therefore, within this paper, the unit roots test, specifically the Augmented Dickey-Fuller test, is performed in order to test for possible unit root. **Table 3** gives evidence of the unit root results. Thus, it could be concluded that not all the variables are stationary in their level form. Regarding the first three variables, it can be concluded that they are stationary in their level form, given that the *t*-statistic value is much lower than the critical values and the *p*-value is essentially zero. Based on the results from ADF, CPI and IR became stationary in the first difference. Given that VECM requires the same order of integration, the first difference has been considered for all the variables. See **Tables 3** and **4**.

Table 3. ADF statistics for unit root tests in level form.

Variables	ADF	Critical value at 1% level of significance	Critical value at a 5 % level of significance	Probability
LLOANS	−8.654084	−4.186481	−3.518090	0.0000
LGDP	−6.684869	−4.186481	−3.518090	0.0000
LFDI	−5.959258	−4.186481	−3.518090	0.0001
CPI	−2.290782	−4.192337	−3.520787	0.4295
IR	−1901160	−4.186481	−3.518090	0.6366

Table 4. ADF statistics for unit root tests after taking the first difference.

Variables	ADF	Critical value at 1% level of significance	Critical value at 5 5 % level of significance	Probability
LLOANS	−7.389532	−4.198503	−3.523623	0.0000
LGDP	−7.506682	−4.198503	−3.523623	0.0000
LFDI	−5.774146	−4.234972	−3.540328	0.0002
CPI	−10.73632	−4.192337	−3.520787	0.0000
IR	−9.055130	−4.192337	−3.520787	0.0000

4.2. Cointegration

Having checked for the stationarity of the data, the next step we followed was the cointegration test to detect the relationship of the variables in the long run. Henry and Juselius (2000) state that as long as the data are cointegrated in the level form, cointegration would also exist in the logarithm form. Keeping that in mind, we have converted the data into logarithms to ensure the variables' comparability and applied the test that way. After conducting the Johansen test and considering both the Trace and Max-eigenvalue tests, we identified some cointegrating relationships among the variables, as shown in **Table 5**. Furthermore, the Johansen test yielded one to two cointegrating relations based on different data trend setups at the section of linear cointegrating equations with intercept and trend and no trend in both Trace and Max-Eigen value reports for two cointegrating relations. Regarding the above results, we conclude that the time series are cointegrated, implying a long-term equilibrium relationship among them; therefore, it is possible to proceed further with the Vector Error Correction Model.

Table 5. Summary of cointegration relation (Johansen test).

Data Trend	**None**	**None**	**Linear**	**Linear**	**Quadratic**
Test Type	No intercept No Trend	Intercept No Trend	Intercept No Trend	Intercept Trend	Intercept Trend
Trace	1	2	2	2	2
Max-Eig	0	1	2	2	2

4.3. Vector Auto Regression model

Before applying the VAR model, it is important to determine the optimal lag length based on the VAR structure. The lag length criteria test, conducted using E-Views, helps identify the appropriate number of lags by considering various criteria: the LR test statistic, Final Prediction Error (FPE), Schwartz Criterion (SC), Akaike Information Criterion (AIC), and Hannan-Quinn Criterion (HQ). As shown in **Table 6**, most criteria suggest using two lags in the model.

Table 6. Lag length criteria test.

Lag	**LogL**	**LR**	**FPE**	**AIC**	**SC**	**HQ**
0	−229.6643	NA	0.064422	11.44704	11.65601	11.52313
1	−128.7553	172.2836	0.001605	7.744160	8.997993	8.200736
2	−69.87242	86.17003*	0.000325	6.091338	8.390032*	6.928395*
3	−41.74966	34.29605	0.000325*	5.939008*	9.282563	7.156546

Another step before proceeding with VAR is also the inverse roots of the AR characteristic polynomial, so it is possible to check if all the roots fall into the unit root circle to enable the stability of the model (Brooks, 2008). **Table 7** and **Figure 1** display the results of a stability test for a Vector Autoregressive (VAR) model based on the roots of its characteristic polynomial. All roots in the VAR model fall within the unit circle, confirming its stability. This stability test suggests that the model's predictions will not diverge over time.

Table 7. Inverse roots of AR characteristic polynomial.

Root	**Modulus**
0.894044	0.894044
0.701943	0.701943
−0.236165 − 0.648788i	0.690434
−0.236165 + 0.648788i	0.690434
0.453968 − 0.474731i	0.658807
0.453968 + 0.474731i	0.658807
−0.467596 − 0.145769i	0.489791
−0.467596 + 0.145769i	0.489791
0.205899 − 0.442847i	0.488372
0.205899 + 0.442847i	0.488372

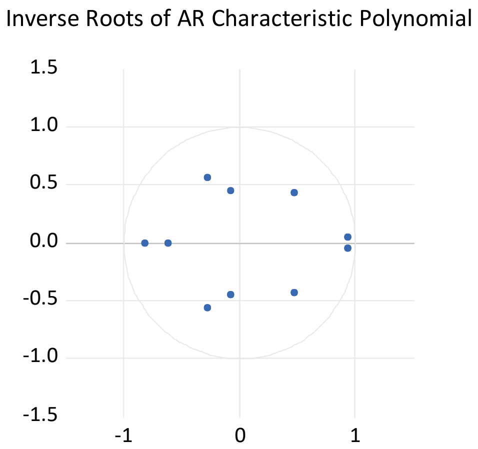

Figure 1. Inverse roots of AR characteristics polynomial using two lags.

Table 8. VAR model.

Variables	DLLOANS	DLGDP	DLFDI	DIR	DCPI
DLLOANS(−1)	−0.873698 (0.18385) [−4.75230]	0.342513 (0.36405) [0.94083]	0.147280 (0.51769) [0.28450]	0.542071 (0.31281) [1.73289]	0.318865 (0.166227) [0.192431]
DLLOANS(−2)	−0.290997 (0.18946) [−1.53590]	0.420980 (0.37518) [1.12209]	−0.452162 (0.53350) [−0.84753]	0.199244 (0.32237) [0.61806]	0.860108 (1.71306) [0.50209]
DLGDP(−1)	−0.040331 (0.08337) [−0.51614]	−0.796542 (0.16509) [−4.82490]	0.337437 (0.23476) [1.43738]	0.322695 (0.14185) [22.7485]	0.500245 (0.75380) [0.66363]
DLGDP(−2)	−0.049819 (0.08184) [−0.60874]	−0.298499 (0.16206) [−1.84193]	−0.409013 (0.23045) [1.77486]	0.099557 (0.13925) [0.71496]	7.836605 (0.73996) [10.59061]
DLFDI(−1)	−0.064135 (0.06501) [−0.98646]	−0.423861 (0.12874) [−3.29232]	0.513129 (0.18307) [−2.80287]	0.133713 (0.11062) [1.20874]	0.863181 (0.58784) [−1.46840]
DLFDI(−2)	−0.057053 (0.06738) [−0.84667]	−0.249642 (0.13344) [−1.87089]	−0.112792 (0.18975) [−0.59444]	0.368216 (0.11465) [3.21154]	−0.781315 (0.60927) [−1.28239]
DIR(−1)	0.001579 (0.09848) [0.01603]	−0.201012 (0.17905) [−1.12263]	0.389472 (0.25462) [1.52963]	0.379023 (0.15385) [2.46355]	−1.351811 (0.89041) [−1.51819]
DIR(−2)	−0.139910 (0.09042) [−1.54728]	−0.201012 (0.17905) [−1.12263]	0.389472 (0.25462) [1.52963]	0.379023 (0.15385) [2.46355]	0.592635 (0.81757) [0.72488]
DCPI(−1)	−0.002832 (0.00974) [−0.29086]	0.007717 (0.01928) [0.40028]	0.001105 (0.02741) [0.04031]	−0.010435 (0.01656) [−0.62995]	−0.129772 (0.08803) [−1.47424]
DCPI(−2)	−0.005985 (0.00872) [−0.68601]	0.005745 (0.01728) [0.33254]	0.007366 (0.02457) [0.29983]	−0.010798 (0.01484) [−0.72739]	0.005880 (0.07888) [0.07454]
C	0.044529 (0.03555) [1.25273]	−0.030456 (0.07039) [−0.43270]	0.067783 (0.10009) [0.67721]	−0.077189 (0.06048) [−1.27627]	0.383812 (0.32139) [1.19423]

Table 8. (*Continued*).

VAR model explanatory metrics					
Metric	**DLLOANS**	**DLGDP**	**DLFDI**	**DIR**	**DCPI**
R-squared	0.598377	0.563851	0.524631	0.413352	0.873460
Adj. *R*-squared	0.464502	0.418468	0.366175	0.217802	0.831279
Sum sq. resids	1.113613	4.366673	8.829913	3.223945	91.03853
S.E. equation	0.192667	0.381	0.201134	0.283618	0.255464
F-statistic	4.469688	0.381518	0.542522	0.327818	1.742015
Log likelihood	15.74574	-12.26528	-26.70023	-+.045668	-74.529555
Akaike AIC	-0.231500	1.134892	1.839036	0.831496	4.172173
Schwarz SC	0.228239	1.594631	2.298774	1.291235	4.631912
Mean dependent	0.028072	0.014055	0.028072	-0.131863	0.553659
S.D. dependent	0.263286	0.500297	0.681448	0.370659	4.240996

After confirming the number of lags and the stability criteria using the inverse roots of the AR characteristic polynomial, the next step is to estimate the basic VAR model. Based on the unit root test results, some variables became stationary at the first difference, so the data is converted to its first difference before applying the VAR model. According to Brooks (2008), the hypothesis of the VAR model is tested using the *t*-statistic, which is then compared with the *t*-critical value. In this model, the *t*-statistic is shown in brackets, while the *t*-critical values are derived from the *t*-table for 40 observations and 28 degrees of freedom. At a 1% significance level, the t-critical value is approximately 2.467, and at a 5% significance level, it is approximately 1.701. Results of VAR are presented in **Table 8,** and based on it, when the variable loan is considered endogenous, both lags are strongly negative (−8.737 and −0.2910), meaning that previous increases in loans significantly decline the present rate of changes in loans. As for GDP, coefficients are still negative but very small, indicating a small, moderate impact of past GDP changes in current loan growth. The same conclusion also stands for FDI, which has a light negative impact on loans. In the VAR model, interest rates have mixed effects: one positive and one negative, showing a delayed negative impact on loan growth. CPI has a small negative effect, meaning it has little influence on loan growth. Overall, loan growth seems to depend mostly on its own past trends. In the alternative scenario, where GDP is treated as endogenous, both loan coefficients are moderately positive, indicating that previous loan growth positively contributes to GDP growth. Regarding FDI being endogenous, one coefficient of loans is positive while the other is negative; thus, this suggests a mixed impact of FDI on loans. Regarding interest rates, both coefficients of loans are positive, indicating that previous loan growth attempts to boost interest rates. Lastly, when taking CPI as endogenous, both lags of loans are positive, implying a strong positive impact of loans in CPI. Thus, this also indicates that the growth in loans pushes inflation pressures.

4.4. VAR residual serial correlation LM test

The VAR residual serial correlation test gives evidence of the possible correlation between the residuals in the model. The primary goal of this test is to assess whether there is any autocorrelation in the residuals (errors) of the VAR model at various lags, which would suggest model misspecification. Based on the results provided in **Table 9**. The *p*-values across all lags are above the typical 0.05 threshold, so we fail to reject the null hypothesis at any lag. This suggests that there is no evidence of serial correlation in the residuals of the VAR model at these lags, which indicates that the model is well-specified concerning autocorrelation.

Table 9. VAR residual serial correlation LM test.

Lag	**LRE* Stat**	**df**	**Prob.**	**Rao F-stat**	**df**	**Prob.**
1	33.30665	25	0.1236	1.405440	(25, 79.5)	0.1292
2	28.32959	25	0.2929	1.161390	(26, 79.5)	0.3011
3	31.46243	25	0.1742	1.313449	(25, 79.5)	0.1809

4.5. Heteroscedasticity test for the residuals of a VAR model

Table 10 represents the results of the heteroscedasticity for the VAR model. The tests show that the VAR model's residuals mostly have constant variance, meaning the assumption of homoscedasticity is met. This supports the reliability of the model's estimates. The stability and variance tests confirm that the model is well-designed and statistically sound.

Table 10. Heteroscedasticity test for the residuals of a VAR model.

Chi-sq	**df**	**Prob.**
317.6911	300	0.2310

4.6. Normality test

Table 11 represents the VAR residual normality test results specifically for the Doornik-Hansen test for multivariate normality. Skewness: All components have *p*-values less than 0.05, indicating significant skewness (non-normal) for each component. Kurtosis: None of the individual components have *p*-values below 0.05, suggesting the kurtosis is not significantly different from normal for each component. Jarque-Bera test: Components 1, 2, 3, and 5 have significant *p*-values (all below 0.05), indicating non-normality in these components; component 4 is not significant (*p*-value > 0.05). The joint Jarque-Bera test has a *p*-value of 0.0000, confirming that the overall residuals are not normally distributed. Overall results indicate significant skewness and acceptable kurtosis. The VAR model generally shows robust diagnostic results: there is no indication of autocorrelation, and the absence of heteroskedasticity confirms the model's stability. The inverse roots are within the unit circle, showing that the model fits well. The high *R*-squared and adjusted *R*-squared values mean the VAR model explains much of the data's variation. The observed non-normality in the residuals, indicated by the skewness and Jarque-Bera tests, could plausibly be attributed to the relatively low number of observations. Moreover, the VAR model is robust to moderate skewness, especially in macroeconomic analysis, when data can naturally deviate from perfect normality. The skewness values are somehow high for components 2 and 5, but considering the other diagnostics, they are unlikely to distort the results significantly.

Table 11. VAR residual normality test.

Component	**Skewness**	**Chi-sq**	**df**	**Prob.**
1	-1.321082	10.67246	1	0.0011
2	-1.738393	15.70098	1	0.0001
3	-1.207704	9.325228	1	0.0023
4	-0.233297	0.470880	1	0.4926
5	1.976818	18.55113	1	0.0000
Joint	-	54.72068	5	0.0000
Component	Kurtosis	Chi-sq	df	Prob.
1	7.191417	2.768141	1	0.0962
2	8.199432	0.030683	1	0.8610
3	5.942808	0.718263	1	0.3967
4	2.574848	0.038277	1	0.8449
5	10.45888	0.223428	1	0.6364
Joint	-	3.778764	5	0.5817
Component	Jarque-Bera		df	Prob.
1	13.44060		2	0.0012
2	15.73166		2	0.0004
3	10.04346		2	0.0066
4	0.509157		2	0.7752
5	18.77456		2	0.0001
Joint	58.49944		10	0.0000

4.7. Vector Error Correction Model

Having applied the VAR model and considering the results from cointegration (Johansen test), which indicates cointegrating relations among the variables within the model, we proceed with the Vector Error Correction Model (VECM), which enables us to distinguish short-run and long-run relations among the variables. Based on the results of VECM presented in **Table 12**. In the long term, there is a negative relationship between loan growth and GDP, indicating that increases in GDP growth decline the loan growth. Moreover, a positive relation between loans and FDI indicates that FDI contributes to loan growth. Similarly, in the context of interest rates, the results show a negative relationship between loans and interest rates in the long run, meaning that the higher the interest rates, the lower the credit will be. As for CP, there is a positive effect on loan growth; higher inflation boosts credit growth in the long term. The small negative coefficient in the error correction term indicates that in case of deviation from the long-term equilibrium loans, however, slowly adjust back to it. Lastly, regarding short-run dynamics, VECM confirms the results of the previous VAR analysis.

Table 12. Vector error correction model.

Variable	**CoinEq1**
DLLOANS(−1)	1.000000
DLGDP(−1)	−23.49600 (5.69231) [−4.12767]
DLFDI(−1)	15.73947 (2.53951) [6.19783]
DLIR(−1)	−2.141643 (2.15166) [−0.99535]
DLCP(−1)	1.268871 (0.47494) [2.67167]
C	−1.108358

Error Correction Estimates

Variable	**D(DLLOANS)**	**D(DLGDP)**	**D(DLFDI)**	**D(DIR)**	**D(DCPI)**
CointEq1	−0.006144 (0.01032) [−0.59527]	−0.006306 (0.01746) [−0.36127]	−0.134029 (0.01750) [−7.65777]	0.024885 (0.01540) [1.61593]	−0.290099 (0.06524) [−4.44638]
D(DLLOANS(−1))	−1.174475 (0.17584) [−6.67916]	0.133296 (0.29739) [0.44822]	0.720175 (0.29819) [2.41518]	0.173130 (0.26236) [0.65989]	1.107745 (1.11186) [0.99657]
D(DLLOANS(−2))	0.549031 (0.17391) [−3.15707]	0.191697 (0.29411) [0.65178]	0.022725 (0.29490) [0.07706]	0.053815 (0.25947) [0.20740]	1.110615 (1.09932) [1.01028]
D(DLGDP(−1))	−0.171333 (0.22644) [−0.75665]	−1.328010 (0.38295) [−3.46781]	−2.483152 (0.38398) [−6.46686]	0.733744 (0.33785) [2.17182]	−6.534487 (1.43138) [−4.56518]
D(DLGDP(−2))	−0.166207 (0.19773) [−0.84059]	−0.657030 (0.33440) [−1.96479]	−1.780063 (0.33530) [−5.30887]	0.560753 (0.29501) [1.90076]	1.390764 (1.24991) [1.11270]
D(DLFDI(−1))	0.021079 (0.14485) [0.14553]	−0.452238 (0.24497) [−1.84611]	0.641397 (0.24563) [2.61128]	−0.282685 (0.21611) [−1.30804]	2.614998 (0.91862) [2.85597]
D(DLFDI(−2))	−0.022857 (0.09686) [−0.23598]	−0.402156 (0.16381) [−2.45495]	0.387330 (0.16425) [2.35812]	0.040685 (0.14452) [0.28152]	0.952783 (0.61229) [1.55609]
D(DIR(−1))	−0.054362 (0.15013) [−0.36209]	−0.729808 (0.25391) [−2.87429]	−0.491113 (0.25459) [−1.92903]	−0.494865 (0.22400) [−2.20920]	−2.167825 (0.94904) [−2.28422]
D(DIR(−2))	−0.223461 (0.13430) [−1.66396]	−0.814956 (0.22712) [−3.58816]	−0.541463 (0.22773) [−2.37762]	0.059703 (0.20037) [0.29796]	−1.815280 (0.84893) [−2.13832]

Table 12. (*Continued*).

Error Correction Estimates					
Variable	**D(DLLOANS)**	**D(DLGDP)**	**D(DLFDI)**	**D(DIR)**	**D(DCPI)**
D(DCPI(−1))	−0.006791 (0.01440) [−0.47152]	−0.001605 (0.02436) [−0.06588]	−0.014707 (0.02442) [−0.60220]	0.006804 (0.02149) [0.31667]	−0.424106 (0.09104) [−4.65856]
D(DCPI(−2))	−0.007042 (0.01031) [−0.68304]	0.005414 (0.01744) [0.31052]	−0.014910 (0.01748) [−0.85282]	−0.002849 (0.01538) [−0.18519]	−0.192590 (0.06517) [−2.95509]
C	−0.001187 (0.04154) [−0.02857]	0.024298 (0.07025) [0.34581]	0.011291 (0.07044) [0.16028]	0.012643 (0.06198) [0.20398]	0.041589 (0.26259) [0.15833]
Explanatory Metrics					
Metric	**D(DLLOANS)**	**D(DLGDP)**	**D(DLFDI)**	**D(DIR)**	**D(DCPI)**
R−squared	0.793144	0.818780	0.903976	0.628192	0.964418
Adj. R−squared	0.711879	0.747587	0.866252	0.482124	0.950439
Sum sq. resids	1.921098	5.494826	5.524355	4.276637	76.76617
S.E. equation	0.261936	0.442994	0.444183	0.390816	1.655792
F−statistic	9.759980	11.50078	23.96300	4.300690	68.99172
Log likelihood	3.962109	−17.05609	−17.16328	−12.04329	−69.79523
Akaike AIC	0.401895	1.452805	1.458164	1.202165	4.089762
Schwarz SC	0.908558	1.959468	1.964828	1.708828	4.596425
Mean dependent	−0.007054	0.001929	0.001422	0.009539	−0.007500
S.D. dependent	0.487987	0.881743	1.214557	0.543074	7.437652

4.8. Granger causality

To deepen the empirical testing, we proceed with the Granger causality test. Bressler and Seth (2011) state that Pairwise Granger Causality and VAR Granger Causality/Block Exogeneity Wald Tests are performed to detect the relationship among variables in the short run by specifying this relationship as uni-directional or bi-directional. Results of the Granger causality test, which focuses only on the relationship of loans with other variables, are presented in **Table 13**. The hypothesis for each variable has been set by Brooks (2008). The paper's results reveal that only one uni-directional relationship runs from FDI to loans.

Table 13. Granger causality test.

Null Hypothesis	**Chi-Square**	**Probability**
DLLOANS Does Not Granger Cause DLGDP	0.706589	0.7024
DLLOANS Does Not Granger Cause DLFDO	0.454977	0.7965
DLLOANS Does Not Granger Cause DCPI	3.820048	0.1481
DLLOANS Does Not Granger Cause DIR	0.479967	0.7866
DLGDP Does Not Granger Cause DLLOANS	0.425625	0.8083
DLFDI Does Not Granger Cause DLLOANS	11.50217	0.0032
DIR Does Not Granger Cause DLLOANS	0.581996	0.7475
DCPI Does Not Granger Cause DLLOANS	1.172431	0.5564

4.9. Variance decomposition

The last test to be applied to this VAR model is variance decomposition. Therefore, this test helps detect the contribution of various shocks to the variance of variables in the system over time. It provides evidence of the dynamic interactions among the variables within a system. Results of the variance decomposition for loans are presented in **Table 14**.

Table 14. Variance decomposition test.

Period	S.E.	DLLOANS	DLGDP	DLFDI	DIR	DCPI
1	0.261936	100.0000	0.000000	0.000000	0.00000	0.000000
2	0.269192	97.43047	0.430549	1.070224	0.386520	0.682237
3	0.326792	95.26916	0.325048	2.209849	1.419543	0.776397
4	0.340722	92.11888	0.666999	3.005738	3.068406	1.139976
5	0.358099	89.55681	0.608469	2.876780	5.923622	1.034317
6	0.374028	89.73043	0.705907	2.639722	5.972461	0.951479
7	0.390057	89.70482	0.768464	2.647139	5.933958	0.945620
8	0.396920	89.63800	0.754269	2.951962	5.736341	0.919424
9	0.420598	90.13213	0.737485	2.991702	5.171005	0.967680
10	0.424972	90.03273	0.874161	3.020288	5.119815	0.953011

Initially, 100% of loan variance is self-explanatory, but this decreases over time as FDI and interest rates exert greater influence. The impact of GDP and CPI is less significant in explaining loans over time. The results reveal that loan-related factors, such as credit conditions, market liquidity, or previous lending decisions, mostly influence loan growth.

4.10. OLS regression

Table 15 presents the OLS results. GDP shows a positive but insignificant effect on loans, meaning it has little impact. FDI has a significant negative effect, indicating it reduces loans. Interest rates also have a significant negative effect, showing a strong link to lower loan growth. CPI has a small negative effect, but it is not statistically significant, meaning inflation has little impact on loans. As for model fit statistics, the R square is 0.276988, meaning the model explains 27.7% of the variation in DLLOANS. Moreover, indicator saturation suggests an indicator saturation method was applied, testing for structural breaks with 43 indicators over two blocks. Two indicators (ISPERIOD(“2020Q2”) and ISPERIOD(“2020Q3”)) were detected as significant, likely marking structural changes in these periods. The coefficient for ISPERIOD(“2020Q2”) is positive and statistically significant, claiming a positive impact on loans during this period, potentially due to some external events such as COVID-19. The same conclusion is also driven for the period 2020Q3. The R square is 0.707136, indicating that the model explains approximately 70.7% of the variation in DLLOANS. The F-statistic is statistically significant. The findings from Durbin Watson (2.386257) indicate no strong evidence of autocorrelation. Overall, the model explains the variance in loans, with interest rates being the most influential variable.

Table 15. OLS regression.

Variable	Coefficient	Std. Error	t-Statistic	Prob.
DLGDP	0.011318	0.049706	0.227705	0.8212
DLFDI	-0.118869	0.037093	-3.199191	0.0029
DIR	-0.340065	0.062454	-5.445028	0.0000
DCPI	0.004354	0.005856	0.743415	0.4621
C	-0.025281	0.025681	-0.984442	0.3315
@ISPERIOD('2020Q2')	-0.687009	0.155534	-4.417106	0.0001
@ISPERIOD('2020Q3')	0.882127	0.155106	5.687201	0.0000
Statistic	**Value**			
R-squared	0.707136			
Adjusted *R*-squared	0.658325			
S.E. of regression	0.152625			
Sum squared resid	0.838601			
Log likelihood	23.63589			
F-statistic	14.48733			
Prob(*F*-statistic)	0.000000			
Mean dependent var	0.027070			
S.D. dependent var	0.261108			
Akaike info criterion	−0.773762			
Schwarz criterion	−0.487055			
Hannan-Quinn criter.	−0.668033			
Durbin-Watson stat	2.386257			

In terms of OLS regression, we have also conducted the normality test. **Figure 2** represents the results obtained from this test. The test's finding indicates that the mean is very close to zero; therefore, this is an assumption of the well-specified model where the residuals should ideally have a mean of zero. The median is also very close to zero. The skewness is slightly positive, which claims a minor rightward skew but is close to zero and indicates approximate symmetry. Moreover, kurtosis is slightly less than normal, implying that the distribution is flatter than normal, with lighter tails. Regarding these findings, the Jarque-Berra test, which consists of skewness and kurtosis, indicates that the residual distribution can be considered approximately normal. In summary, the residual diagnostics suggest that the model is appropriate, and the assumptions underlying OLS regression (like normally distributed errors) are reasonably satisfied.

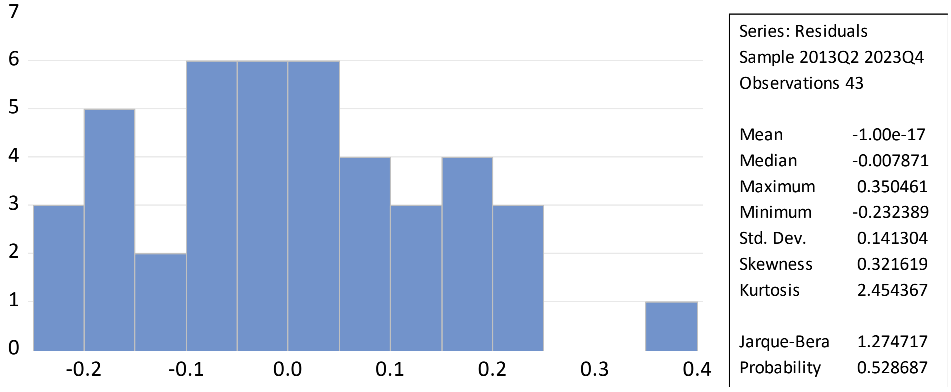

Figure 2. Descriptive statistics.

We have conducted the VIF, autocorrelation, and heteroscedasticity tests to further explain the model. **Tables 16–18** give evidence of the findings from these tests. VIFs are around or slightly above, suggesting very low multicollinearity among the variables in these modes. This implies that the independent variables are not highly related to each other. All test statistics, including the Breusch-Pegan-Godfrey test and the regression of squared residuals, indicate no significant evidence of heteroscedasticity in the model. The residuals appear to have a constant variance. Regarding autocorrelation, the findings indicate that there is no sign of autocorrelation.

Table 16. Variance inflation factors.

Variable	Coefficient Variance	Uncentered VIF	Centered VIF
DLGDP	0.002471	1.070940	1.068802
DLFDI	0.001376	1.110950	1.108601
DIR	0.003901	1.184493	1.033018
DCPI	3.43e-05	1.092036	1.080571
C	0.000659	1.217377	NA
@ISPERIOD('2020Q2')	0.024191	1.038475	1.014324
@ISPERIOD('2020Q3')	0.024058	1.032767	1.008750

Table 17. Heteroscedasticity test.

Statistic	Value	Prob.
F-statistic	0.530009	0.7817
Obs**R*-squared	2.490100	0.7453
Scaled explained SS	1.778894	0.9389

Table 18. Autocorrelation test.

Statistic	Value	Prob.
F-statistic	2.167511	0.1300
Obs*R-squared	4.862550	0.0879

5. Contribution

5.1. Interpretation of long-run dynamics

The long-run negative nexus between credit growth and GDP is one of the most striking results within this paper, implying that economic growth leads to less credit growth. The paper's results contradict the traditional view that GDP growth should be associated with more credit. However, this negative relation might indicate that businesses and households might have enough capital as GDP increases, thus decreasing the need for credit or external funding. On the other hand, the positive correlation between FDI and credit growth underlines the importance of foreign direct investments in boosting credit activity. These results align with the present literature, implying that FDI is a key source for the growth and financial development of the banking sector.

Moreover, the negative relation between credit growth and interest rates confirms the standard perception in monetary economics that higher interest rates lead to less credit growth. When interest rates increase, the cost of lending increases as well, which makes credit less attractive to businesses and consumers. In addition, this relationship can also be explained in terms of monetary policy. Policymakers can use interest rates as a very effective tool to moderate rapid credit growth or, on the other hand, to boost lending when there is low economic activity, implying that interest rates' traditional role in this aspect remains robust.

The paper shows a positive link between CPI and credit growth over the long term. This means that during times of higher inflation, businesses and households may borrow more to cover their expenses. This could also be due to looser monetary policy, where banks lend more even with rising prices. This should be carefully studied. Lending during inflation could lead to financial instability.

5.2. Interpretation of short-run dynamics

A different scenario regarding the short-run dynamics obtained from the VAR model exists. Credit growth in the short run is mostly driven by its lagged values, suggesting that the credit market has strong persistence. In other words, this means that lower growth often follows times of rapid credit growth because banks adjust their credit portfolios, and the borrowers pay the existing debts. This cyclical attitude is in line with the credit cycles theory.

In addition, the short-run moderate impact of GDP on credit growth suggests that changes in economic activity do not immediately lead to changes in credit activity. This might be because banks and borrowers might take time to adapt to new economic conditions, or another reason might be that other factors might have a better impact in shaping short-run credit dynamics.

Moreover, mixed results of interest rates in credit growth in the short run underline the complexity of monetary transmission mechanisms. While interest rates are a key determinant for credit activity in the long-run periods, they might not stand in the short run due to external shocks, time lags, and market expectations, and credit activity might be less predictable. The results of OLS are also almost in line with the VAR model.

5.3. Granger causality

The Granger causality test within this paper provided additional analysis regarding the relationship between credit growth and other variables in the paper. The finding that only one directional relationship runs from FDI to credit growth aligns with the notion that FDI is a key indicator that can influence credit growth. The absence of a bi-directional relationship between these two variables might indicate that although FDI greatly impacts banking activity, credit activity might not be a key factor for FDI. The absence of Granger causality relations among other variables might imply that short-term factors like interest rates, GDP, and CPI might not have immediate predictive power over credit growth. This highlights that credit activity is impacted by external and structural factors that do not always align with short-term economic changes.

5.4. Variance decomposition

The variance decomposition test has further deepened the analysis within this paper. The finding that loan growth within this paper is mostly driven by its shocks reveals that internal banking sector factors such as liquidity, credit policies, and risk play a more significant role in credit growth than macroeconomic factors. However, the increasing impact of factors like FDI and interest rates over time points out the importance of monetary policy and capital flows in the credit activity of banks. These results suggest better risk management actions and sound monetary policy to guarantee financial stability because the banking sector is vulnerable to external shocks in the long run.

5.5. Implications for policy and practice

This paper provides key policy implications for evaluating credit expansion. Policymakers should critically assess credit growth indicators, as high economic growth may lead banks to prioritize credit quality over quantity, resulting in slower credit growth despite favorable macroeconomic conditions. The positive relationship between foreign direct investment (FDI) and loan growth underscores the importance of creating a conducive environment for FDI. Policymakers can achieve this by improving regulatory transparency and reducing barriers to entry.

The findings on interest rates and consumer price index (CPI) highlight the traditional role of monetary policy in moderating loan growth. Policymakers should continue using interest rate adjustments to manage credit activity while considering inflation's influence on credit expansion. Striking a balance between loan growth and price stability will enhance financial and economic stability.

6. Summary

This paper aimed to investigate the determinants that could impact credit growth by focusing on the case of Kosovo. The paper analyzed factors such as GDP, FDI, interest rates, and CPI, thus examining their interaction with credit growth. The dataset covered the period from 2013 to 2023, and due to data availability, some of the data were converted into quarterly frequencies to make them comparable. The tests were conducted using a dataset of 45 observations. Firstly, the Augmented Dickey-Fuller test provided evidence of the stationarity of the data. The Johansen cointegration test indicated that there are long-run relationships among the variables, enabling the use of the VECM. The optimal lag length criteria also provided evidence of the appropriate lags to use within the model and facilitated the establishment of a proper VAR model. Finally, inverse roots of the AR characteristics polynomial confirmed the stability of the model, and descriptive statistics provided evidence of the distribution of residuals. OLS regression was also conducted to verify whether VAR's results aligned with it.

Results from the above analysis imply that loan growth is primarily driven by its previous values; however, prior FDI and GDP also have a considerable negative effect on current loan growth. The VAR model indicated that the impact of interest rates was mixed in the short run, with the relationship among these variables being unclear and potentially varying based on monetary policies and economic conditions. The impact of CPI was very small. The model also considered an alternative scenario, treating other variables as endogenous. In that case, loans positively impacted GDP, inflation, and interest rates. From the Granger causality relations and in response to the paper's research questions regarding this test, the results indicate only one unidirectional relationship, which runs from FDI to loans. OLS regression confirmed the results of VAR, showing that GDP has no impact on loans, FDI has a small negative impact, interest rates have a strong negative impact, and CPI has no impact.

In addition, the VECM results differentiated between the short- and long-run dynamics among the variables in the model. The results provided evidence of a negative relationship between loans and GDP, suggesting that GDP growth reduces loan growth. This could be due to improved financial conditions among individuals, leading to a reduced need for borrowing. The impact of interest rates remained negative in the long run, indicating that higher interest rates reduced loan growth by making borrowing more expensive. Finally, the results demonstrated a positive relationship between loans and FDI. Based on the VECM results, FDI contributes to loan growth, possibly because FDI stimulates economic activity, increasing the demand for credit. The Granger causality test also confirmed the relationship between loans and FDI. There is also a positive relationship between loans and CPI in the long term, indicating that higher inflation translates into higher credit growth over time. This could be because, during periods of inflation, people and businesses may finance purchases to avoid future price increases.

This study highlights the critical role of FDI and macroeconomic factors in influencing credit expansion. However, the paper has some limitations, such as the specific dataset with a limited sample size and availability that may influence the findings. The model did not account for shocks that might have impacted the relationship between loans and other factors included in the paper. Additionally, due to the reliance on publicly available data, the paper only considered some factors that could impact loan growth, while in practice, other factors may also play a role.

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